

Generalized algorithm for efficient multi-channel data fusion and real-time implementation using wavelet transform

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Hamid Krim, Viraj Mehta

With Clay Gloster (Howard Univ.), Tom Conte (NCSU) and Tom Flatley (GSFC-NASA)

Vision, Information and Statistical Signal Theories and Applications Group (VISSTA)

Outline

- **Motivation**
- **Problem formulation**
- **Bayesian Estimation for fusion**
- **Numerical optimization for real-time implementation**

Multispectral remote sensing

- Some recent instruments (satellite based)
 - Landsat mission:
 - **Multi-Spectral Scanner (MSS) – 4 bands**
 - **Thematic Mappers – 7 bands**
 - Terra:
 - **Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) – 14 bands**
 - **Moderate Resolution Imaging Spectrometer (MODIS) – 36 bands**
 - EO-1:
 - **Hyperion – 220 bands**
 - **Advanced Land Imager (ALI) – 10 bands**

Characteristics of sensor measurements

- **Sizable acquired data at different resolutions**
- **Missing/erroneous data**
- **Non-stationarity**
- **Multispectral/hyperspectral**
- **High-resolution (as low as 1m)**
- **Correlated channels**
- **Spatial dependencies**

Objectives

- **Data exploitation for analysis and interpretation:**

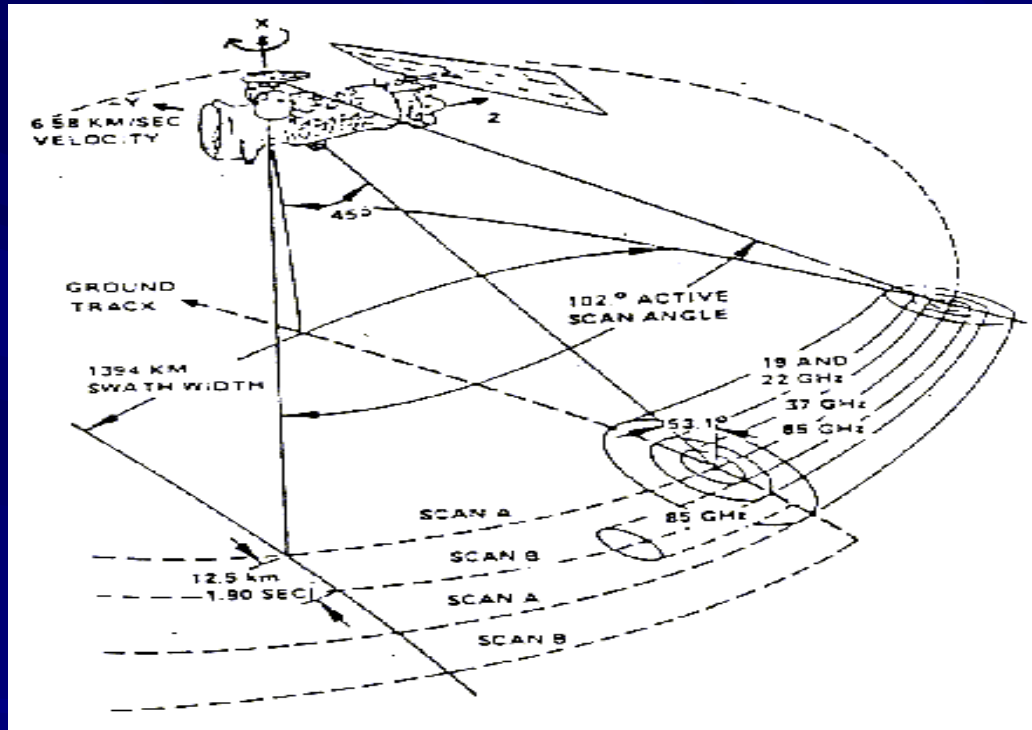
- Coherent & composite image by *sensor Fusion*
- Enhanced resolution of fused data by *Optimal Estimation*
- Parsimonious and flexible representation of non-stationary data by *Statistical Transformations*

- **Processing guidelines:**

- Memory efficiency
- Real-time implementation
- FPGA compatible algorithms
- Minimize communication burden

The SSM/I instrument

- **Special Sensor Microwave/Imager**



- **Problem: Jointly exploit channels for resolution enhancement**

Problem Formulation

- The channel measurements Y are given as:

$$Y = GX + E$$

where

G = The antenna gain function

X = The true underlying temperature field

E = Measurement error

- Assuming Gaussian model for X and E ,
with *Bayesian Estimation* we have:

$$\hat{X} = (P^{-1} + G^T R^{-1} G)^{-1} G^T R^{-1} Y$$

P = *a priori* Covariance Matrix of X

R = *a priori* Covariance Matrix of E

Formulation for SSM/I

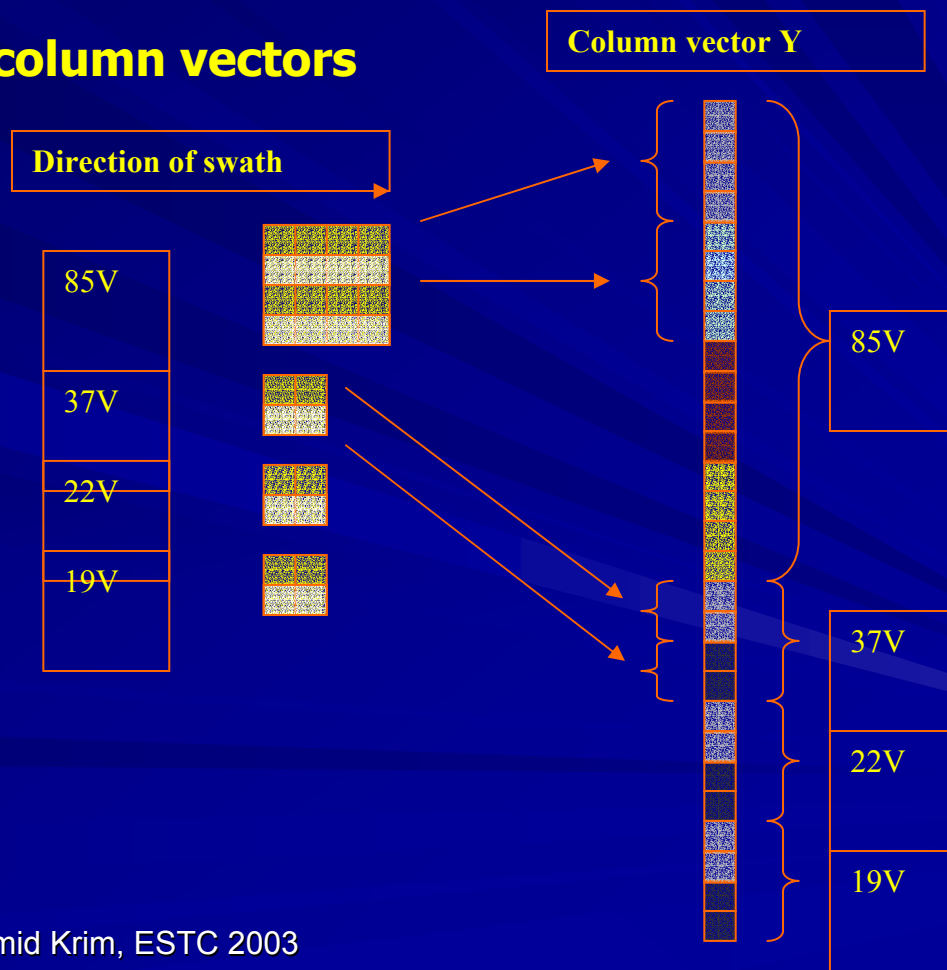
- Format *stationarized* vertical polarization channels at each frequency from the seven available data channels

- Vectorize 2-D data into 1-D column vectors

$$\mathbf{Y}_{85} = \text{Vec}[\mathbf{Y}_{85}]$$

- Append all channels

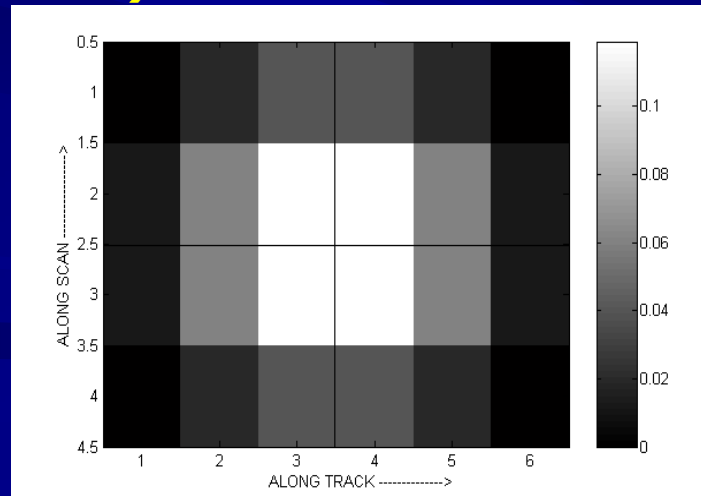
$$\mathbf{Y} = [\mathbf{Y}_{85}, \mathbf{Y}_{37}, \mathbf{Y}_{22}, \mathbf{Y}_{19}]^T$$



Receive Antenna model

▪Hypotheses

- Local stationarity over 10x10 pixel patches in the 85V channel
- Estimated field finer in resolution 4 times in each dimension than the 85V channel i.e. pixel width = $12.5/4 = 3.125\text{km}$
- Each of the four channels has a jointly binomial gain pattern
- Example: Gain pattern for the 85V channel (note implied overlap along track)



Construction of statistical models

- Empirically estimate *a priori* covariance matrices
 - P of the field
 - Challenge from non-stationarity
 - R of the measurement error
 - Use as weights on channels

Field prior covariance model

▪ Assumptions and method

▪ Use 85V channel

- Closest in resolution to underlying field
- Channel with least overlap of footprints
- No overlap in scan direction

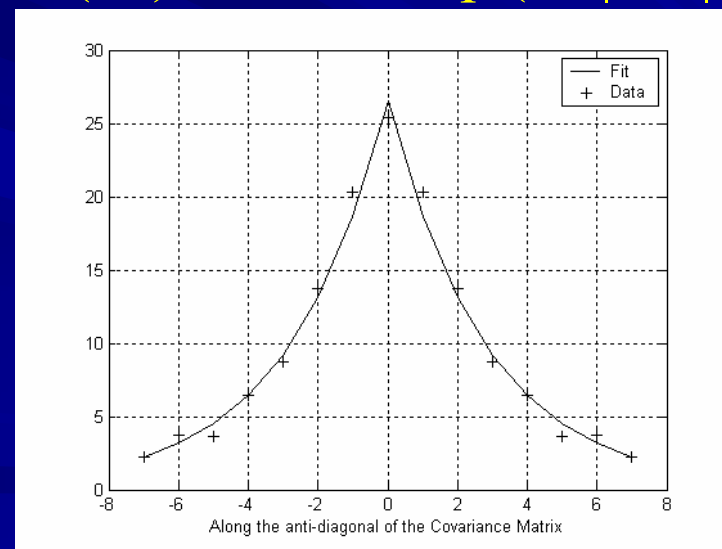
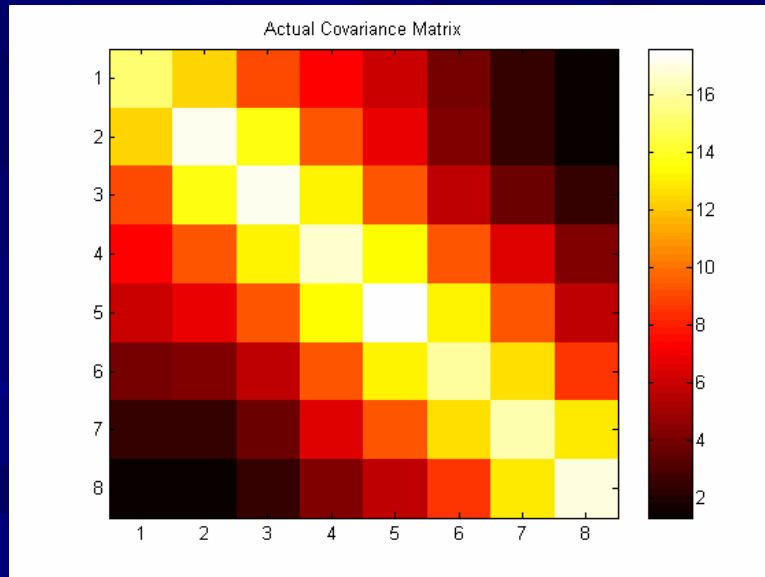
▪ Windowing

- Local stationarity in general
- Global stationarity achieved for locally detrended data
- Mean normalization over 8x8 shifting window

Field prior covariance model

- **Assumptions and method**
- **Compute statistics for along scan direction**
 - **Fits to exponential model in the anti-diagonal**
 - **Only two parameters required to define model**

$$C(d) = A * \exp(B |d|)$$



Field prior covariance model

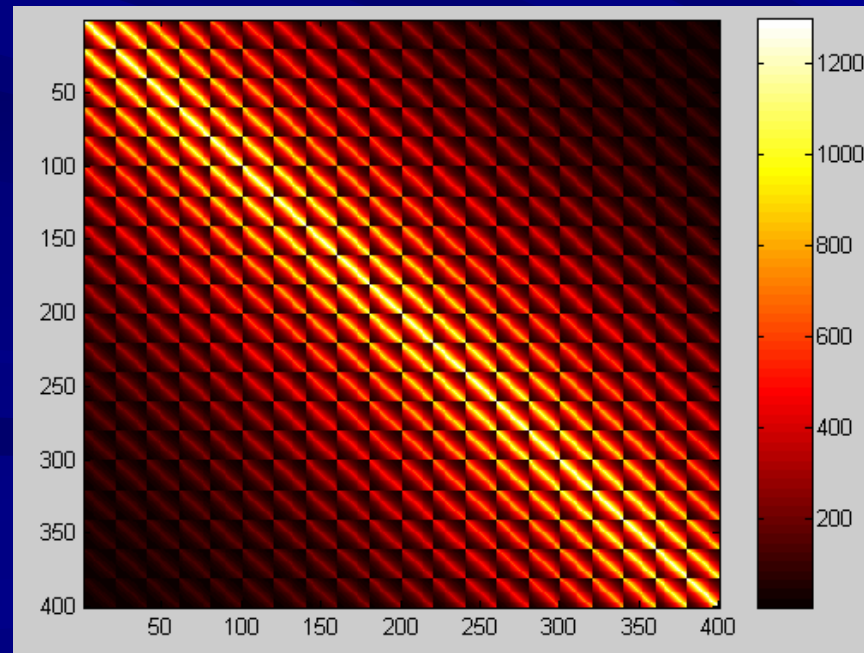
- Assume isotropy

- Mathematical model for vectorized data of NxN

$$P(x, y) = C(d) =$$

$$= C(\sqrt{(\lfloor x/N \rfloor - \lfloor y/N \rfloor)^2 + (x - \lfloor x/N \rfloor - y + \lfloor y/N \rfloor)^2})$$

$$= A * \exp\{-B * \sqrt{(\lfloor x/N \rfloor - \lfloor y/N \rfloor)^2 + (x - \lfloor x/N \rfloor - y + \lfloor y/N \rfloor)^2}\}$$



More Generally...

- **Observe characteristics of sample data to determine what input channel(s) provide statistical data that is closest to the underlying field and thus has minimum overlap**
- **Apply statistical normalization (e.g. detrend) to selected data to guarantee the imposed assumptions of stationarity**
- **Compute the covariance matrix for the relevant input data points**
- **Construct a field covariance model**
- **Using model, solve for field estimate of a specified swath length.**

Error prior covariance model

▪ Assumptions

- Zero mean additive white gaussian noise
- Non-correlation and equal variance for given channel
- For each channel covariance matrix is diag. $\sigma^2 \mathbf{I}$
- Interpret the error variance as a weighting factor
- Higher error variance for a particular channel implies less reliance on the channel in estimating underlying field
- Impose $\sigma_4^2 > \sigma_3^2 > \sigma_2^2 > \sigma_1^2$

Prior of measurement error

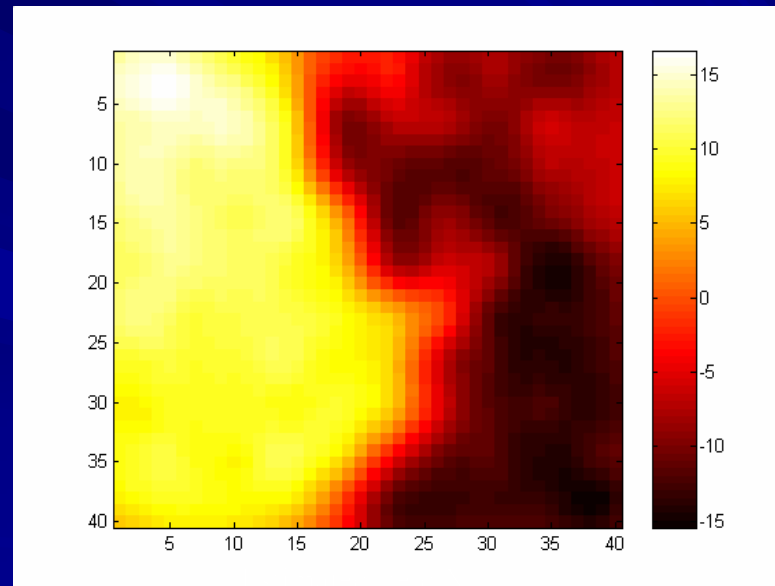
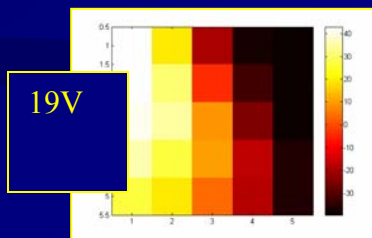
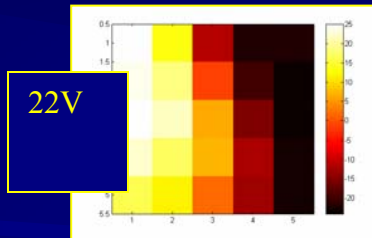
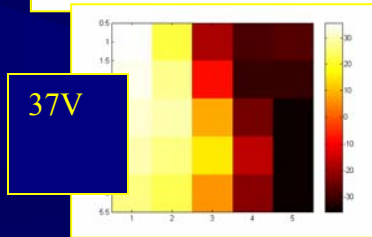
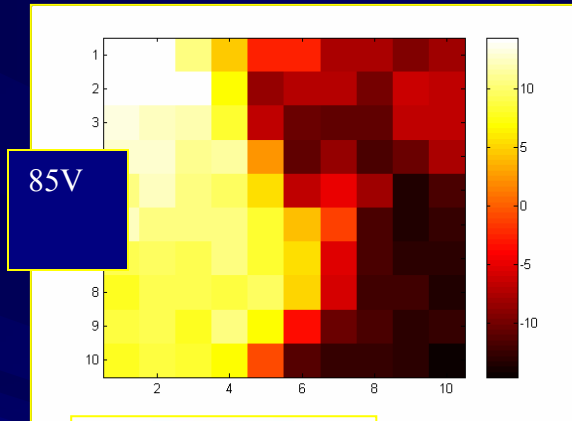
- **Final Covariance Matrix**

$$\mathbf{R} = \begin{bmatrix} \sigma_1^2 I_{n^2 \times n^2} & 0 & 0 & 0 \\ 0 & \sigma_2^2 I_{n^2/4 \times n^2/4} & 0 & 0 \\ 0 & 0 & \sigma_3^2 I_{n^2/4 \times n^2/4} & 0 \\ 0 & 0 & 0 & \sigma_4^2 I_{n^2/4 \times n^2/4} \end{bmatrix}$$

- **Zeros indicate assumption of independence of measurement errors of various channels**
- **Note size dependency on field size for different channels**

Direct method experiment

$$\hat{\mathbf{X}} = (\mathbf{P}^{-1} + \mathbf{G}^T \mathbf{R}^{-1} \mathbf{G})^{-1} \mathbf{G}^T \mathbf{R}^{-1} \mathbf{Y}$$



Pre-whitening manipulation...

- Take Cholesky Factorization of Field priori covariance matrix

$$\mathbf{P} = \mathbf{A}\mathbf{A}^T$$

- \mathbf{A} is a full rank Upper Triangular matrix

- Let $\mathbf{F}_W = \mathbf{A}^{-1}$

- Rewrite problem statement

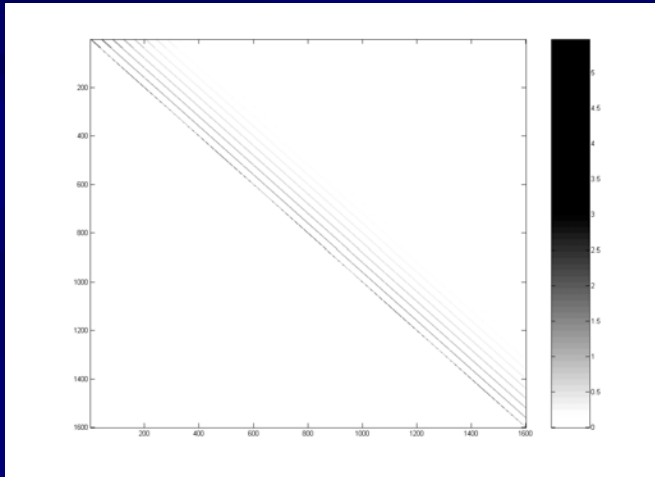
$$\mathbf{Y} = \mathbf{G}\mathbf{F}_W^{-1}\mathbf{F}_W\mathbf{X} + \mathbf{E} \qquad \mathbf{G}_W = \mathbf{G}\mathbf{F}_W^{-1}$$

- The estimation solution now is:

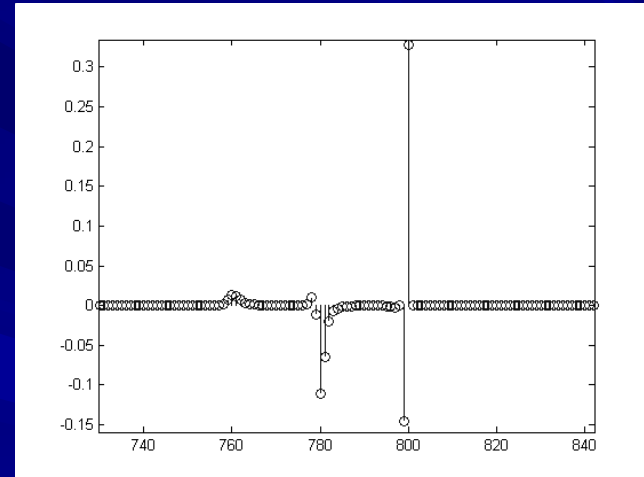
$$\hat{\mathbf{X}}_W = \mathbf{F}_W \hat{\mathbf{X}} = (\mathbf{I} + \mathbf{G}_W^T \mathbf{R}^{-1} \mathbf{G}_W)^{-1} \mathbf{G}_W^T \mathbf{R}^{-1} \mathbf{Y}$$

Pre-whitening transform

- The matrix F_W is in effect a whitening filter.



Inverse filter matrix

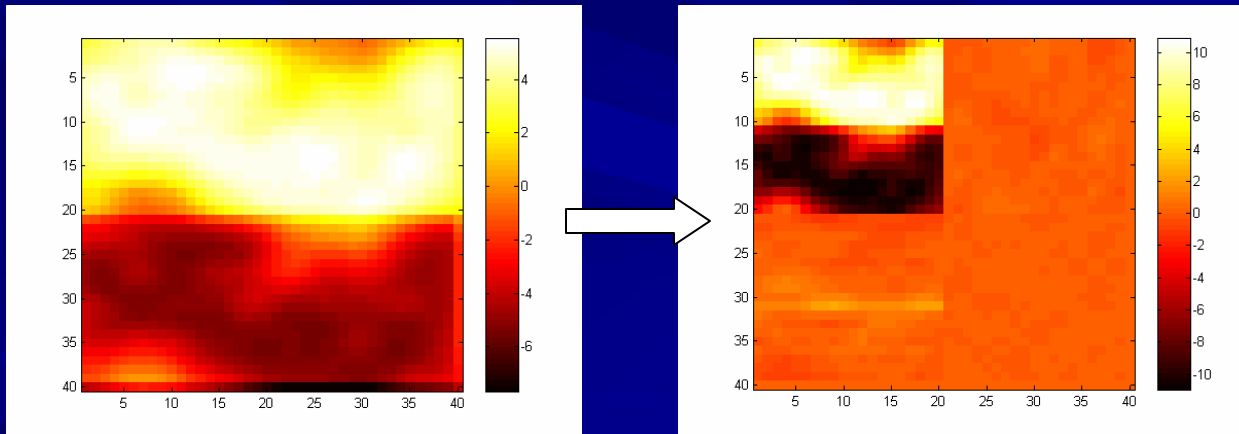


**Impulse response
of whitening filter**

- We use F_W^{-1} i.e. A to “recolor” the estimated quantity as the final step in estimation process

Wavelet/Sparse preconditioning

- Take advantage of sparseness resulting from wavelet transform
- Simplified choice of a suitable wavelet with pre-whitening in place
- Level-1 wavelet decomposition of the estimated quantity (reformatted as 2-D image) using a 2-D Haar wavelet.



Wavelet preconditioning

- Thus, application of a wavelet transform to the vectorized white data

- Threshold and preserve significant portion of information
- Data size reduction by a factor of 4

- Defining

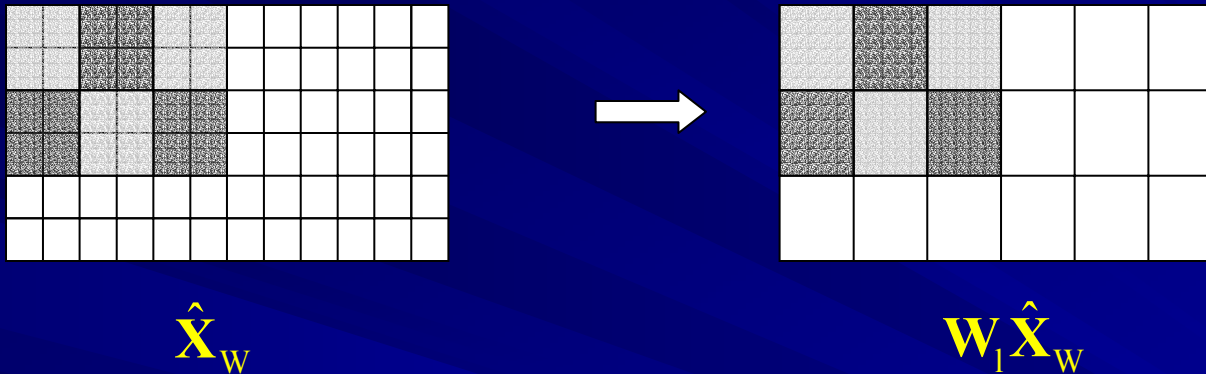
$$\mathbf{X}_1 = \mathbf{W}_1 \mathbf{X}_w \quad \mathbf{G}_1 = \mathbf{G}_w \mathbf{W}_1^T$$

- We have

$$\hat{\mathbf{X}}_1 = \mathbf{W}_1 \mathbf{F}_w \hat{\mathbf{X}} = (\mathbf{I} + \mathbf{G}_1^T \mathbf{R}^{-1} \mathbf{G}_1)^{-1} \mathbf{G}_1^T \mathbf{R}^{-1} \mathbf{Y}$$

Effect of preconditioning

- Haar wavelet transform



- Size reduction of matrices X_1 and G_1 by a factor of 4 in both dimensions

- Significant decrease in computational cost in inverting

$$(\mathbf{I} + \mathbf{G}_1^T \mathbf{R}^{-1} \mathbf{G}_1)^{-1}$$

- Compact representation reduces communication burden for satellites with a small added overhead from preconditioning transforms

Real-time implementation

- **Estimation based on**

- **Decorrelating input channels**
- **Combination of decorrelated channels**
- **Reconditioning of combined preconditioned estimation**

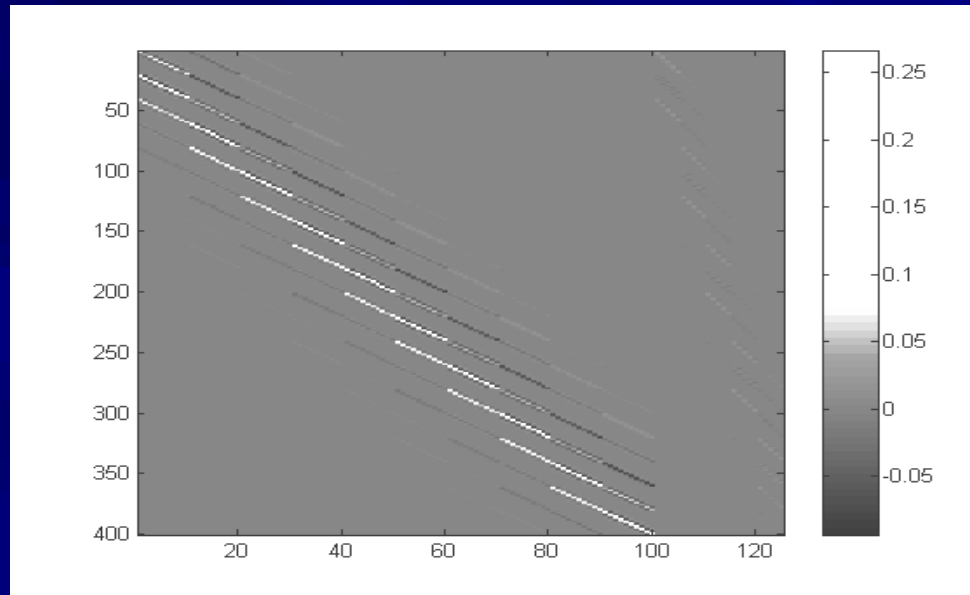
$$\hat{\mathbf{X}}_1 = \mathbf{W}_1 \mathbf{F}_w \hat{\mathbf{X}} = (\mathbf{I} + \mathbf{G}_1^T \mathbf{R}^{-1} \mathbf{G}_1)^{-1} \mathbf{G}_1^T \mathbf{R}^{-1} \mathbf{Y}$$

- **Consider,**

$$\mathbf{M} = (\mathbf{I} + \mathbf{G}_1^T \mathbf{R}^{-1} \mathbf{G}_1)^{-1} \mathbf{G}_1^T \mathbf{R}^{-1}$$

Real-time implementation

▪Note: only 85V and 37V used for this portion for simplified analysis



$$\mathbf{M} = (\mathbf{I} + \mathbf{G}_1^T \mathbf{R}^{-1} \mathbf{G}_1)^{-1} \mathbf{G}_1^T \mathbf{R}^{-1}$$

Real-time implementation

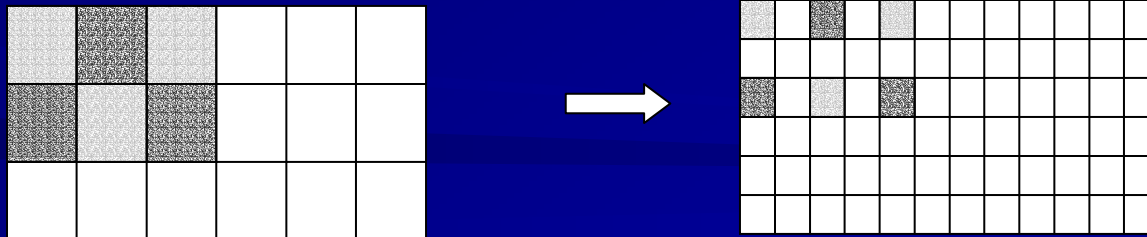
▪ Observations:

$$\mathbf{M} = [\mathbf{M}_{85} \quad \mathbf{M}_{37} \quad \dots]$$

$$\hat{\mathbf{X}}_1 = \mathbf{M}\mathbf{Y}$$

$$= [\mathbf{M}_{85} \quad \mathbf{M}_{37} \quad \dots] \cdot \begin{bmatrix} \mathbf{Y}_{85} \\ \mathbf{Y}_{37} \\ \dots \end{bmatrix} = \mathbf{M}_{85} \mathbf{Y}_{85} + \mathbf{M}_{37} \mathbf{Y}_{37} + \dots$$

▪ Input regridding by insertion of zero points



Real-time implementation

- **Modified input:**

$$\mathbf{Z}_{85}, \mathbf{Z}_{37}, \dots$$

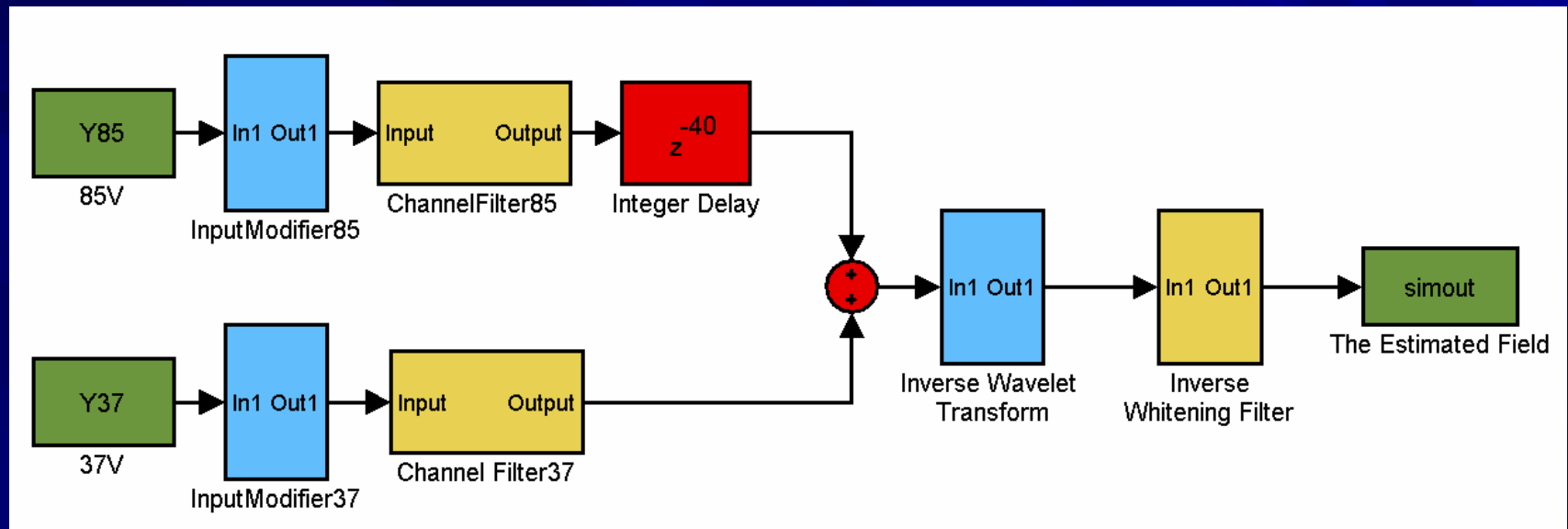
- **Modified operators are channel filters**

- **Resulting estimation process:**

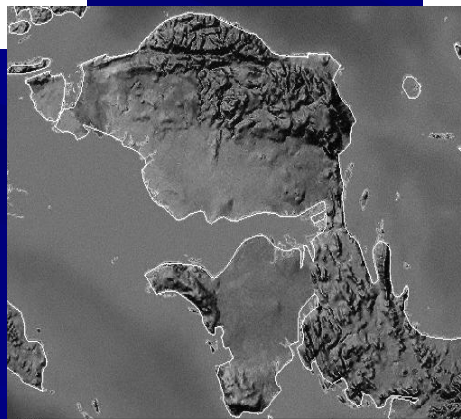
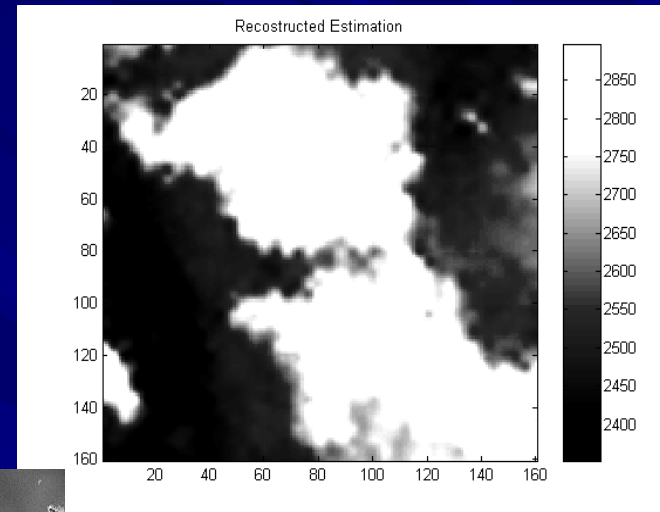
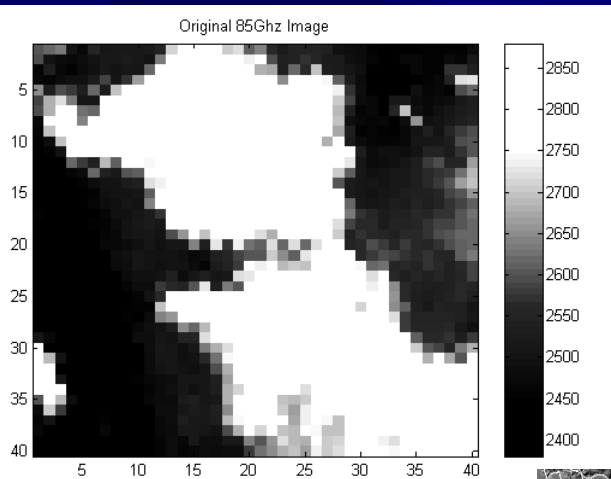
$$\therefore \mathbf{X}_1 = \mathbf{F}_{85} \mathbf{Z}_{85} + \mathbf{F}_{37} \mathbf{Z}_{37} + \dots$$

$$\therefore \mathbf{X}_1 = \mathbf{f}_{85} * \mathbf{Z}_{85} + \mathbf{f}_{37} * \mathbf{Z}_{37} + \dots$$

Block diagram



Simulation result



Comparison of original input 85GHz data with reconstructed estimation fusion result

Conclusions

- ✓ **An optimal Bayesian estimator for data/sensor fusion developed**
- ✓ **Empirical analytical models may be constructed and utilized in improving computing efficiency**
- ✓ **Further improvement and potential near- or real time implementation**
- ✓ **Simplified and adapted algorithmic architecture for Hardware transitioning**

Future Work

- **Efficient adaptation to non-stationarity**

- Real-time empirical estimation of covariance model parameters
- Input data from 85V channel may be used on account of least overlap direction and isotropy
- Prediction based on feedback from estimated underlying field

- **Adapting to instrumental errors**

- Adaptively control the variance of error measurement for every channel in the error covariance matrix

- **Investigate other data (e.g. Hyperion data)**

Thank You!